

Active Vibro-Tactile Sensing for Non-Destructive Selective Harvesting of Strawberries in Precision Agriculture

by

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Submitted to the Department of Robotics
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Abstract

In recent decades, precision agriculture has attracted growing interest, both for reducing farmers' manual workload and for supporting the Sustainable Development Goal of achieving zero hunger. With continued population growth, the development of novel technology-driven harvesting methods has become increasingly important. One promising direction is the integration of intelligent robotic systems into orchards and greenhouses to monitor crop conditions and perform harvesting in a timely manner. To achieve this, robots must be equipped with robust sensory feedback. For ripeness estimation, vision-based methods are the most widely used; however, they often suffer from occlusions caused by branches and foliage and may provide unreliable assessments for fruits whose ripeness is not clearly visible from external appearance alone. In contrast, touch offers a natural means of assessing fruit firmness, which is closely related to ripeness. Traditional tactile approaches, however, often rely on passive procedures such as squeezing and observing indentation, which can bruise soft ripe fruit. This thesis proposes a non-destructive tactile sensing method based on active vibrational feedback, which enables a robot to establish light contact with a strawberry and estimate its ripeness prior to grasping. The sensor was further integrated with a robotic arm and gripper to emulate a realistic selective strawberry-harvesting scenario with adaptive grasping based on the estimated ripeness. Through vibrational signal analysis and statistical validation, the system achieved a classification accuracy of 71% on previously unseen strawberry samples. These results demonstrate the potential of the proposed approach for affordable and scalable robotic harvesting.

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Chapter 1

Introduction

1.1 Haptics and Sense of Touch

Touch is a special skin sense that provides us with information about temporal and spatial events on our bodies. One can barely imagine their life without tactile perception, which allows them to perform basic tasks such as knowing if their cup of coffee is too hot or finding a coin in their pocket. We usually take touch for granted until something hinders it and changes how we perform a task, for example, inserting a key into a door lock with numb fingers due to cold weather. Indeed, touch seems to be one of the most important senses since it is the first sensory system to develop [2] and usually the last one to deteriorate [12], thus serving as a means of communication and protection almost lifelong. Furthermore, vision- or hearing-deprived people can still rely on tactile sensing as touch conveys information in various forms such as temperature, vibrations, pressure, pain, stretch, and others [25], [30]. In contrast, certain people who are insensitive to pain or extreme temperatures are perpetually exposed to danger and injuries [24].

In fact, tactile sensing, together with kinesthesia (the sense of limb position and movement), forms a highly complex and interrelated system, namely, haptics [11]. Haptics, unlike other perception systems, is bidirectional, meaning the *action can be performed for perception* and *the perception can be performed for action*. The former constitutes the active movement of a hand – an essential part of haptic perception – to

perform *exploratory procedures*. For example, lateral motion is executed to assess the texture, a static contact is used to perceive temperature, and applying pressure helps to identify an object's compliance (Fig. 1-1). Collectively, these interactions form a basis of haptic perceptual experience and provide information about the object's properties. Exploratory acts may irreversibly change the property of a target object, unlike in vision or hearing. For example, applying too much force on a ripe strawberry may bruise it, while looking at a tree or listening to music does not change its state. Still, for tasks such as texture recognition or compliance estimation, haptics is usually the sense of choice.

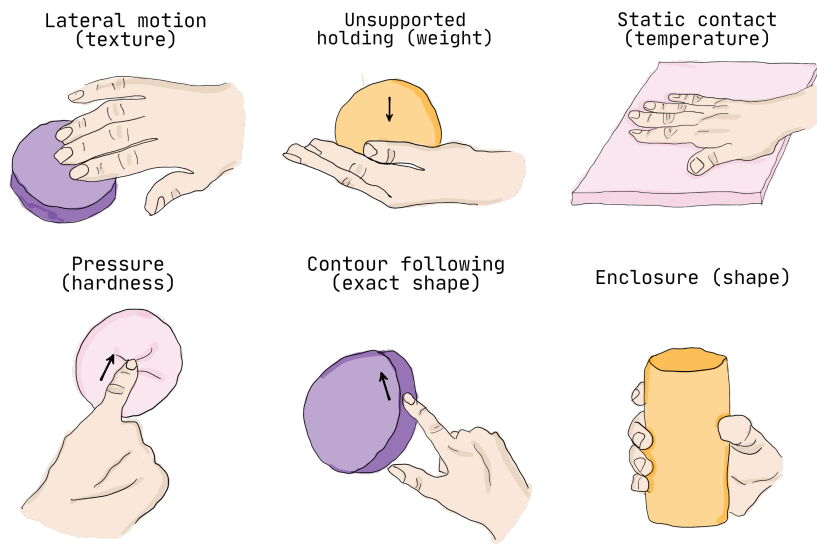


Figure 1-1: Exploratory procedures that we perform to understand an object's properties using haptics and tactile sensing.

Understanding an object's properties, such as compliance and shape, can be essential for controlling and modulating force when we manipulate it. Sensory signals from tactile receptors contribute to adjusting the magnitude, direction, timing, and spatial distribution of grip forces. It is especially important to respect the safety margin when exploring a fragile object to avoid damaging or slipping it during active exploration. With deprived tactile feedback, due to anesthesia, for example, it would be impossible to control grip forces adequately. That being said, haptics is a complex system that comprises multiple highly interrelated touch circuits under the skin that provide us with essential tactile feedback, allowing us to perform dexterous manipu-

lation tasks. So, replicating a human touch artificially might be seen as a daunting engineering task, but it is highly worthy to explore.

1.2 Difficulty of Skill Transfer

As the humanoid and anthropomorphic robots increasingly participate in human daily lives, it is essential to ensure these agents interact in a safe and predictable way. This can be achieved by equipping the robots with different sensors, replicating the human perception system. Although vision seems to be an obvious feature to introduce for robot navigation and perception, it can be insufficient to achieve accurate results, especially in dark or occlusive environments. Touch, on the other hand, provides a wealth of information about objects' properties and enables dexterity in robotic systems. However, the exploratory motions, which seem to be natural to perform for a human, pose a challenge to a robot. So, the question that comes up is, can we combine and optimize these exploratory procedures, adapting them to a robotic system?

With 38 muscles, 21 degrees of freedom, and thousands of sensory cells in the skin [10], a human hand is capable of highly dexterous tasks that took millions of years to evolve. Replicating these capabilities in a robotic hand is a formidable engineering and scientific challenge. An alternative to complex, time- and space-consuming exploratory movements is active sensing. Tactile sensing is active if it generates energy to the environment to observe the response from a target object, and if the sensor, rather than a test object, stimulates sensing [26]. This approach enables faster identification of object properties without requiring dynamic manipulation of an object.

1.3 Robotic Tactile Perception in Precision Agriculture

One of the major applications of robotic systems is precision agriculture, defined as a farming practice that uses technologies to provide timely, optimized, and precise crop care [14]. This method has become crucial in the realm of global population growth, which creates an increasing strain on the world’s food supply. Traditional farming practices can be inefficient in their use of irrigation water, in the occupation of arable land, and in their reliance on manual labor. One way to relieve the pressure is by introducing sensorized intelligent machines for repetitive tasks such as harvesting throughout the working day without losing precision and productivity.

Compliance, which is closely correlated with ripeness [31], is one of the major food features that is used for efficient robotic harvesting and, thus, delivering fresh and high-quality foods. To estimate the hardness of a fruit or vegetable, touch is generally preferred over vision, as the latter may suffer from occlusions caused by the end-effector and may not be as accurate in this task as its tactile counterpart. Touch perception, in this case, gives more intricate details about the internal structure of a food item, providing deeper insights about its ripeness stage. Furthermore, tactile feedback enables dexterous manipulation tasks such as selective harvesting and crop monitoring [18]. Food item grasping strategy is highly dependent on the features of the target, which are extracted from tactile sensing. For example, ripe items require more delicate manipulation to avoid damage under higher forces. These food properties can be acquired during the pre-grasp phase with a minimal applied force. When a light contact is detected, the system decides the optimal grasping force based on the extracted features. For tactile feedback, capacitive, resistive, and optical sensors can be used; however, these types of sensors rely on passive sensing by deforming the surface of a sample, which potentially leads to its damage and, thus, cannot be used for pre-emptive grasping.

Conversely, active vibrational tactile sensing, as a novel alternative, enables subtle contact detection and non-destructive compliance estimation. Vibrations are indeed

a fair candidate for a tactile sensing modality as they can provide tactile cues that reflect the properties of an observed object non-destructively. As the fruit ripens, its molecular structure undergoes changes, which in turn affect its mass, density, shape, and the modulus of elasticity. These transformations can be captured as a mechanical response in the form of object-modulated vibrations. Since vibrations are extremely sensitive to the slightest changes on their way, they can be used for delicate manipulation tasks, such as touch detection and gentle force control [29].

For this study, I analyzed the vibrational fingerprints of *strawberries* at each ripeness stage because they exhibit relatively pronounced changes in firmness during ripening and are ubiquitous in the consumer market. An active vibro-tactile sensor setup was introduced to a robotic system consisting of a manipulator arm with an end-effector to enable selective harvesting based on the strawberry ripeness. For this, emitted vibrations were used to perform a pre-grasp procedure – touch detection followed by compliance estimation. In the case of a mature sample, force control was executed to separate the berry from the branch, imitating a real harvesting scenario.

Chapter 2

Review on Tactile Sensing

Technologies for Ripeness Estimation

For long times, fruit ripeness assessment relied on destructive techniques, such as the Magness-Taylor (MT) puncture test [22], which, while accurate, damages the fruit and is thus not appropriate for large-scale use. As such, over the past few decades, various types of tactile sensors have been explored to track the ripeness of fruits, vegetables, and berries *non-destructively*. This chapter describes some of them with a focus on the acoustic vibration method since it was used in the main experiments of this thesis.

2.1 Traditional Methods

2.1.1 Electrical Tactile Sensors

Electrical tactile sensors (ETS) are among the first and most common sensing approaches. These sensors produce a change in the electrical signal that was caused by contact with a subject. Piezoresistive sensors are one state-of-the-art example that is widely used for artificial tactile perception due to its simplicity in fabrication and transduction principle, as well as relatively low cost. Their working principle is based on the translation of the changes in mechanical pressure to the changes in

resistance properties of a piezoelectric material. This type of sensors were also applied to estimate fruit ripeness. As such, Erukainure et al. [6] and Christopher et al. [3] developed piezoresistive sensors for mangoes and kiwifruit ripeness detection, respectively. Both studies used a multiple-cantilever arrangement of piezoresistive elements, representing low- and high-stiffness springs (Fig. 2-1(A)). This configuration allowed for differential stiffness measurement by comparing the outputs of individual "springs", thus making the sensing independent of variations in the applied displacement and applied force. Despite covering a wide range of fruit stiffnesses (about 67.81 - 1792.95 N/m), reliable sensor readings were obtained only after a few millimeters of displacement against the sensor's tips (indenters). Even such local indentation may mechanically damage a test fruit, especially a small one such as a strawberry or plum, if it exceeds its bruise threshold (Fig. 2-1(D)). In general, piezoresistive sensors, although affordable in manufacturing, require a complex signal filtering and processing unit. In [6], the authors used a Wheatstone bridge circuit to convert the resistance changes to voltage signals and then feed this output to the DAQ system. Such a sensor setup necessitates bulky and fragile electronic components, compromising the sensor's electronic scalability.

Capacitive sensors are another type of ETS that respond to applied force by changing their capacitance. These usually consist of two conducting substrates separated by an elastic dielectric layer. Similar to their piezoresistive counterparts, capacitive sensors respond to the mechanical pressure, deforming the dielectric material, which, in turn, produces varying capacitance. In [23], the authors assessed a flexible capacitive sensor in determining the ripeness of tomatoes. A sandwich structure comprising a nanoneedle-patterned PDMS substrate between two metal-coated PET films, essentially forming a capacitive element, was introduced (Fig. 2-1(A)). This sensor featured high flexibility and sensitivity ($0.35 - 1.042 \text{ kPa}^{-1}$, depending on the applied pressure), making it suitable for gentle tactile sensing applications, such as ripeness assessment of fruits and vegetables prior to harvesting. However, the sensor raw output values were in the range 11-15 pF, pointing to the major disadvantage of the capacitive sensing – sensor output readout. Such low capacitance values are usually

hard to interpret and convert to a readable signal, unless additional measurement instruments, such as an impedance analyzer, are introduced, thus complicating and increasing the sensor design cost.

A magnetic tactile sensor is another low-force indentation method for assessing fruit ripeness. The transduction principle is generally based on the change in the magnetic field intensity under mechanical stress, which is detected by Hall-effect sensors. To demonstrate this mechanism in practice, the authors of [5] introduced a custom-made soft gripper equipped with magnetic tactile sensors for real-time apricots' firmness estimation and adaptive grasping. Over five consecutive days, the gripper applied periodic 4 kPa probing after establishing a stable grasp of 28 kPa, thereby inducing changes in the magnetic flux measured by the embedded Hall-effect sensors and processed by a multi-task network to predict the probing forces. As ripening progressed, the quantitative estimate of apricot firmness showed a decrease in firmness during the first 3–4 days of storage, followed by a slight increase in the last 1–2 days, which the authors attributed to dehydration-induced tissue stiffening. This work shows that, although magnetic sensing is compatible with soft structures for delicate manipulation, interpreting its output is non-trivial. This is because Hall-sensor signals are affected by mechanical parasitic effects and require special characterization and calibration, which are performed by an additional set of experiments.

Ribeiro et al. [27] designed a magnetic sensor inspired by a ciliary structure often found in living organisms. This structure allows to detect tiny forces due to the extreme softness and compliance, making the fruit exploration, even a small strawberry, totally non-destructive. This method overcomes the disadvantages of the previously mentioned ETS sensors that require inevitable sample indentation to enable sensing, and such a mechanical deformation, even a small and local one, may cause fruit quality deterioration, especially if it has a small size. Nevertheless, the sensing principle depends on scanning the sensor across the fruit surface, which increases system complexity by requiring precise robotic motion and repeatable contact control. This can be challenging not only in terms of algorithm implementation, but also in practical scenarios involving confined workspaces or small fruit samples.

2.1.2 Vision-Based Tactile Sensors

Another type of tactile sensor is vision-based tactile sensors (VTSs), which augment haptic perception with camera-based vision. Such sensors, being extremely sensitive and providing high spatial resolution, are commonly used in texture and shape recognition tasks, but can also be applied for firmness estimation. A popular example of VTS is a commercial GelSight sensor, which consists of an elastomer gel, LEDs as a light source, and a camera [15]. An object in contact gives its shape to the membrane on top of the elastomer gel, while the camera at the bottom captures the produced shades from different angles (Fig. 2-1(B)). Fahmy et al. [7] used the GelSight sensor together with the DIGIT sensor – another state-of-the-art VTS – to develop corresponding datasets for avocado ripeness estimation using image classification transformer models, achieving accuracy up to 92.3% (PoolFormer model). Another study that used the DIGIT sensor installed on a Robotiq 2F-85 gripper to estimate the ripeness of various berries (strawberries, blueberries, and raspberries) [1]. During data acquisition, the berry sample was progressively squeezed by incrementally closing the gripper until the sample became partially deformed, and a tactile image from VTS was recorded after each reduction in gripper width. This approach provided a comprehensive characterization of fruit deformation, without directly measuring force as the main sensing quantity. This allowed for higher sensitivity by capturing subtle surface deformations, which is particularly important when handling soft fruits. Although the proposed pipeline can characterize a wide range of surface deformation states, in gentle fruit grasping tasks, it is often unnecessary to approach the bruising thresholds. Instead, detecting the small deformations seems to be more relevant for secure grasping than characterizing large deformation regimes.

The authors of [19] developed a custom VTS and assessed its sensing by pressing the sensor against the peach while an internal camera observed a multi-layer elastomer illuminated by LEDs. When the peach contacted the elastomer, two image cues changed: brightness variations on the reflective layer and marker motion/distances on the transparent substrate. In their interpretation, the image appearance/deformation

of the elastomer carried information about peach firmness, while the marker displacement carried information about contact force. The contact was driven by a texture analyzer up to 20 N to mimic robotic grasping without damaging the fruit. The paper showed outstanding results for both prediction pipelines: $R^2 = 0.942$, RMSE = 1.115 (ML/CNN) for contact force prediction and $R^2 = 0.878$, RMSE = 0.732 (CNN-LSTM) for firmness prediction. These two frameworks are indispensable in the gentle fruit manipulation task, though the use of VTS can limit the scalability of the system due to the bulky design compared to other tactile sensor types.

In general, traditional tactile sensors, such as ETSs and VTSs, although capable of providing sensitive and information-rich measurements, rely on direct mechanical contact to generate usable sensing signals. This requirement can be problematic in delicate fruit-handling tasks, since even small local indentations may exceed the bruise threshold of soft or small fruits, such as strawberries. In addition, ETSs often require dedicated signal conditioning and calibration, whereas VTSs typically involve bulkier optical hardware and more demanding image-processing pipelines. As a result, despite their effectiveness in controlled ripeness and firmness assessment, their practical deployment in compact, high-speed, or highly delicate manipulation settings remains challenging.

2.2 Acoustic Approaches

Acoustic vibration analysis is becoming a popular method for determining the quality of agricultural products, particularly their ripeness. The setup usually involves an excitation source and sensors, usually in the form of accelerometers or microphones, that capture the response of a test object. When the wave is emitted, it interacts with the tissue of a fruit. As the fruit ripens, its mechanical and physical properties change, altering the acoustic characteristics of the propagating wave. The state of a fruit at a particular ripening stage can be described by its density, elasticity, and shear modulus. These properties can be inferred by examining object-modulated vibrational cues in the time domain through the travel velocity of the wave, or in the

frequency domain via its resonance frequency [20], [13].

Unlike passive vibro-tactile sensing, which involves dynamic physical contact with an object, as in the case of sliding motion for texture recognition or slip detection, its active counterpart is based on the system’s own controlled excitation of an object. This method is attractive since it does not require complex exploratory procedures, which are impractical in constrained environments and can potentially rupture over-ripe samples. Not only that, thanks to its own controlled excitation, active sensing filters out all the noise unrelated to the vibrational cues. The emitted signal can thus be modeled as a force function that makes a fruit perform a simple harmonic oscillation. In this manner, the fruit itself is assumed to be a mass-spring-damper vibrating system with its own natural frequency, defined by its mass, stiffness, and damping parameters [4]. When the frequency of the emitted signal is close to the natural frequency of the fruit, the system vibrates with an amplitude close to its relative maximum. This phenomenon is called a resonance, and it is a fundamental aspect in the context of vibrational sensing.

The excitation methods define whether a fruit will demonstrate free or forced vibration [31], [4]. The former is generally related to the impact method, when an instantaneous force is applied and the system is then allowed to vibrate freely. Conversely, forced vibrations are produced in the case of a constant force, so the behaviour of a fruit is governed not only by its intrinsic mechanical properties, but also by the characteristics of the applied input (Fig. 2-1(C-ii)).

2.2.1 Impact Method

Similar to how we estimate the ripeness of a watermelon by tapping it and listening to the sound produced, the impact method involves a short pulse excitation and analysis of the vibrational response (Fig. 2-1(C-i)). As such, a kiwifruit’s ripeness was measured by exciting the fruit with a sinusoidal pulse of $250\mu\text{s}$ length [20] over 11 consecutive days. A piezoelectric actuator stimulated the fruit from one side, and a piezoelectric sensor captured the vibrational response from the other side. The authors introduced custom stiffness indexes showing the relationship between the

Young's modulus of a fruit specimen and sound propagation velocity, namely,

$$S_3 = \frac{r^2}{\Delta t^2}$$

measured in m^2/s^2 and

$$S_4 = \frac{m}{\Delta t^2 r}$$

measured in MPa , where r is the sample radius, Δt is the elapsed time for wave transmission, and m is the sample mass. The results show a high correlation between the indices and ground-truth firmness values obtained from the destructive MT test ($r = 0.930$ for S_3 and $r = 0.936$ for S_4) [21], meaning that as the fruit becomes more mature, wave propagation speed as well as stiffness decrease. These results were confirmed by another study where a laser pulse (4 mm in diameter, 1064 nm wavelength, and 10 ns duration) was applied to excite an apple sample. The apple absorbed the optical beam, thus producing propagating elastic waves in the specimen that were measured with a laser Doppler vibrometer (LDV). The elastic modulus, which was derived from wave velocity, decreased as the apple aged. Furthermore, the authors examined resonant modes of the apple under the laser pulse excitation. As the apple ripened, the first resonance peak moved to lower frequencies, indicating a progressive reduction in firmness. The results also point to the main limitation of the impact method: the response of a real fruit cannot be described by a single natural frequency, since the measured spectrum is formed by multiple overlapping resonant modes. Because the impulse excitation spreads over a wide range of frequencies, it is hard to determine which peaks correspond to which vibration mode without additional theoretical modeling and mode-shape analysis. In addition to the complicated interpretation of the vibrational spectra, the impact method suffers from limited input repeatability and environmental noise [31].

2.2.2 Swept-Sine Method

The input in the swept-sine method is typically a sinusoid with a gradually increasing or decreasing frequency, called a chirp signal (Fig. 2-1(C-ii)). Such excitation is more effective in terms of providing energy that is concentrated in a narrow frequency band, and so the signal-to-noise ratio (SNR) of the response signal is improved [8]. This allows for scanning through the resonances more cleanly, so that individual modes are easier to identify and track. Kobayashi et al. [17] applied this method to track the ripeness of an avocado sample by stimulating it with a chirp (1 Hz-20 kHz) from an earphone from one side and recording the response using a microphone from the opposite side. The frequency response showed a shift in resonance to lower frequencies as the fruit ripened and became softer, as a general trend. This corresponds to the equation

$$f = \frac{1}{2\pi} \sqrt{\frac{k}{m}},$$

where f is the resonance frequency, k is the stiffness, and m is the mass of the sample. Also, more peaks appeared on the spectrum as time passed, highlighting an additional high-frequency resonance peak due to the rigid seed, whereas the lower-frequency peak progressively decreased due to softening of the tissue. Kataoka et al. [16] compared single-frequency, multi-frequency, linear-sweep, and exponential sweep signals to excite tomatoes and mandarin oranges to determine their storage time using a similar acoustic sensing setup with an excitation source and a microphone. Sweep signals provided the most accurate estimations as they cover possible resonant modes of the samples more effectively. Taniwaki et al. [32] further demonstrated swept-sine excitation (100-1000 Hz) for melon evaluation using an electrodynamic shaker. The vibrational response was measured by LDV, and the shaker motion was monitored with an accelerometer. By computing the transfer function and extracting the resonance frequency, the authors defined an elasticity index, as a nondestructive indicator of fruit firmness, which decreased with ripening.

Overall, active vibro-tactile sensing offers a fast, reliable, and, most importantly, non-destructive method of estimating fruit ripeness. However, existing systems typ-

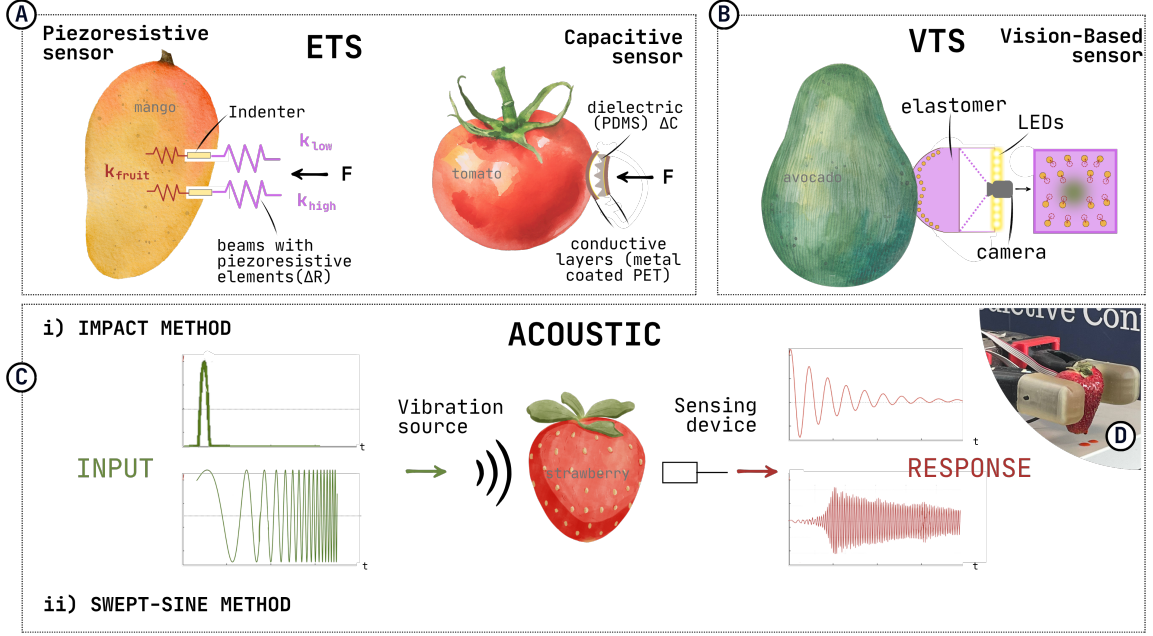


Figure 2-1: Existing tactile sensing methods for fruit firmness estimation. (A) Piezoresistive [6] and capacitive [23] electronic sensors. (B) Vision-based tactile sensor. (C) Acoustic sensing: i) impact method with pulse input and ii) swept-sine method with chirp input. (D) An example of how applying minimum force may bruise a fruit.

ically treat sensing and manipulation as two separate stages, or rely on offline categorical classification rather than continuous real-time evaluation. Consequently, there remains a clear need for an integrated system that unifies active vibro-tactile ripeness sensing with robotic manipulation, enabling accurate non-destructive evaluation, even for small and delicate fruits such as strawberries, and real-time selective grasping based on the acquired tactile information under practical harvesting conditions.

Chapter 3

Methodology

This chapter describes (1) the setup of the proposed tactile sensor on a robotic system, (2) the experimental procedure of detecting the strawberry ripeness, and (3) the data analysis procedure used for fitting a linear model and decision-making algorithm.

3.1 Active Vibro-Tactile Sensor Design

The proposed active vibro-tactile sensor builds on previous work, in which a similar sensor setup was used for contact event detection [29]. In that study, the authors used a coin eccentric rotating mass (ERM) vibromotor as the vibration source ($f_0=120$ Hz) and an ADXL345 analog accelerometer as the sensing device. The vibro-tactile sensor was housed in the Schunk ENG 100 parallel robotic gripper with custom 3D-printed plastic fingers and silicone-molded fingertips, emulating the structure of a human finger with rigid bone and elastic tissue. The sensing principle was rooted in the natural resonance frequency of the system that tended to shift in the case of a contact event. Because the injected vibrations were so sensitive to any disturbances to the system, it was possible to infer a light touch signature in the vibrational response. The same concept of the shifting resonant modes of the system is used in this study to enable the pre-sensing procedure with gentle touch and, thus, avoid a risk of damaging a ripe strawberry with exploratory motions. This study was further extended to the sensing stage, by identifying the ripeness of a strawberry, and the grasping stage, by

separating the berry from a branch with the appropriate force.

The current sensor setup is depicted in Fig.3-1(C). A commercial Robotiq 2-Finger 85 adaptive gripper was used as it matches the payload of the robotic arm manipulator (the gripper weighs 1 kg, which is suitable for a 3 kg manipulator payload [9]) and has sufficient precision for this project (position resolution of 0.4 mm) [28]. Silicone caps for the fingertips were designed to accommodate the vibro-tactile sensor elements. The caps were molded from SORTA-ClearTM silicone rubber with a Shore hardness value of 40A to emulate the soft tissue of a human fingertip pad and avoid applying extensive pressure on a soft specimen. One finger of the gripper acts as a vibration emitter as it houses a linear magnetic ram (LMR) voice-coil haptic motor (TITAN Haptics Inc.) that generates a single-tone signal of 200 Hz for touch detection and a 100-800 Hz linear sweep signal for ripeness estimation. The other finger is the receiving side, as it captures the signal that was propagated through a strawberry's tissue. It also includes an industrial-grade force/torque sensor (Wittenstein HEX-21 F/T sensor) to enable force control required for precise grasping. Both fingers contain three-axis analog accelerometers (ADXL335), which, in fact, define their transmitting or receiving role. This dual configuration allows for decoupling the frequency-response features of the arm-gripper state from those that are intrinsic to the properties of a berry sample.

The STM32F407 Discovery board was used for the data acquisition pipeline, coordinating the pre-sensing and sensing modes of the active vibro-tactile sensor. The firmware was written in the C language using a hardware abstraction layer (HAL) in the STM32CubeIDE software. The on-board digital-to-analog converter (DAC) generates two types of signals: a pure sine wave (200 Hz) for touch detection and a sweep (100-800 Hz of 0.4 s duration) for sensing. At the same time, two on-board analog-to-digital converters (ADCs) connected to their corresponding accelerometers sample the generated signals with a sampling frequency of 8000 Hz, which are then transmitted to a master PC using the UART serial protocol. The frequency of the mono signal for the pre-sensing stage was chosen in an attempt to meet the resonant mode of the system, in particular, the gripper with silicone caps, and produce a

stronger tactile signal from a vibromotor. As such, the resonant mode of the system changed with increasing load, providing a robust signature of contact. On the other hand, for ripeness detection, the sweep signal range was chosen as such to account for the possible natural modes across all ripeness stages of a berry. Compared with impulse-based approaches, which often yield noisy signals that are difficult to interpret, the continuous sweep-signal excitation provides a repeatable and well-controlled broadband stimulus. By examining the "vibrational fingerprint" of a berry, it is possible to infer how its properties evolve as time passes.

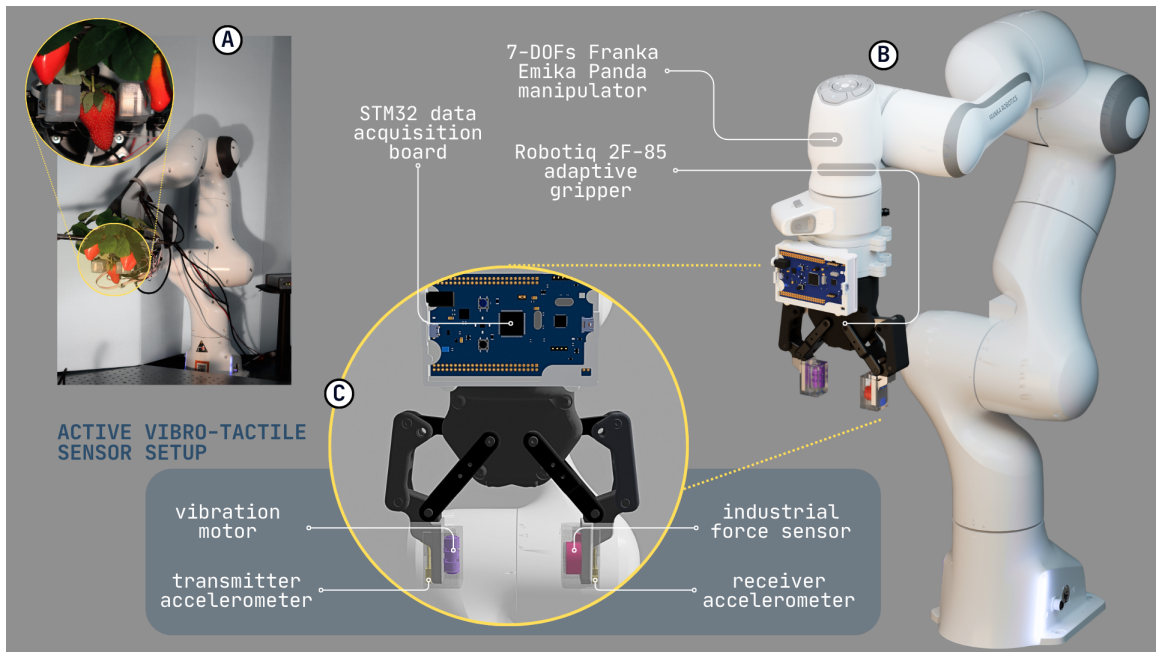


Figure 3-1: Active vibro-tactile sensor setup on an arm manipulator. (A) The real setup of the robot arm in a pose of sensing the ripeness of a strawberry. (B) Representation of the Franka Emika Panda manipulator with Robotiq 2F-85 gripper and vibro-tactile sensor. (C) Zoomed representation of the gripper and the sensor constituents.

3.2 Robotic Arm and End-Effector Configuration

The experimental harvesting scenario was implemented using a Franka Emika Panda 7-DOF manipulator mounted on a rigid base. The `libfranka` C++ library allowed for low-level communication with the robot via the Franka Control Interface (FCI).

To implement the robot control using the Robot Operating System (ROS) framework, the `franka_ros` package was used as a middleware. In this study, the robot operated using three predefined configurations, namely, *home*, *pickup*, and *kneel*. The *pickup* configuration was used for pre-sensing and sensing (Fig.3-1(A)), while the *kneeling* configuration was used during berry detachment. To store joint angles for a specific pose, the Panda was set to the hand-guiding regime, where the end-effector was manually brought up to a berry (pickup pose) and then translated downward (kneel pose). Thus, the motion between the home, pickup, and kneeling poses was executed in joint space using the recorded joint configurations.

A custom-made adapter between the gripper and a robotic arm was designed to attach the Robotiq 2F-85 gripper to the Franka Emika Panda manipulator (Fig.3-2). This coupling consists of electrical and mechanical parts. The former is represented by a printed circuit board (PCB) to provide power and establish communication (RS-485) between the gripper and the PC controller. The latter consists of three mechanical parts: the first one is attached to the manipulator, next a PCB holder goes, and finally the part to attach the Robotiq gripper. In addition, a separate module was designed to attach the STM32 board to the adapter.

The control over the gripper was implemented through a ROS action client-server architecture. The commands were sent to the Robotiq based on the microcontroller's output that was processed through a touch module. That is, completion of the fingers' motion was determined by detecting contact with a strawberry.

The arm manipulator, gripper, and the microcontroller states are managed by a central controller implemented as a ROS node, which enables a coordinated, closed-loop control system for non-destructive sensing followed by adaptive grasping.

3.3 Strawberry Samples

Twelve export-ready strawberries were bought from a grocery store for the training experiments (Fig. 3-3). Five different strawberries at various ripeness stages were prepared for testing the learning model. Each strawberry's stem was placed in a 3D-

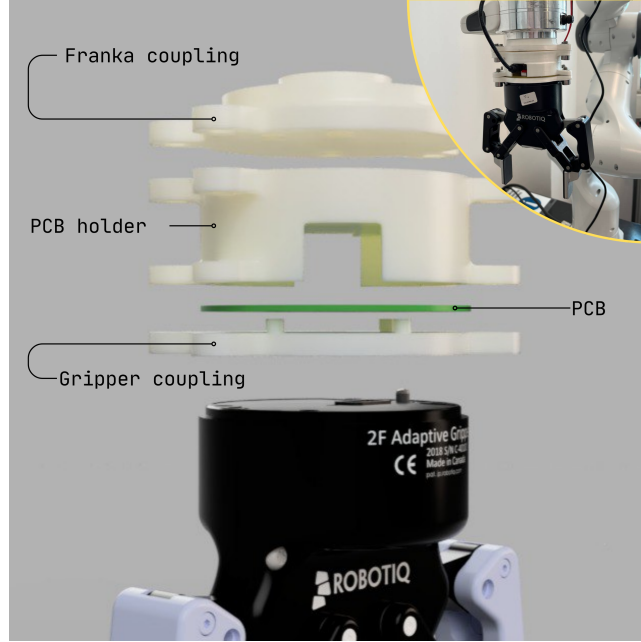


Figure 3-2: Representation of the custom adapter to attach the Robotiq 2F-85 gripper to the Franka Emika Panda arm manipulator.

printed holder with a magnet to attach the sample to an artificial branch with another magnet. Over five consecutive days, the training berries were monitored under room conditions. The gripper approached these strawberries one by one to collect train data each day, corresponding to that specific ripeness stage. To enable non-destructive “harvesting,” the berry samples were gently contacted by the gripper so that they would not be deformed. The vibrotactile sensor integrated into the fingertips was sufficiently sensitive to detect light touch that the industrial force/torque sensor could not measure, yielding output comparable to the noise level.

3.4 Experimental Procedure

A complete state diagram for determining the ripeness of the strawberries non-destructively and collecting the ripe samples is presented in Figure 3-4.

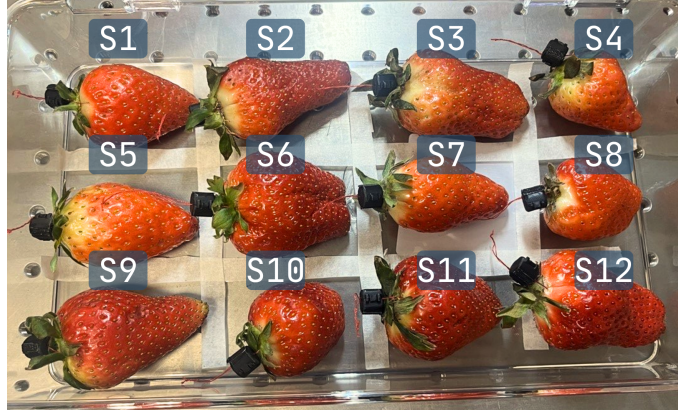


Figure 3-3: Strawberry samples used in the experiments at Day 1.

3.4.1 Supervisor

A ROS super node (supervisor) manages the overall task execution by coordinating the Franka manipulator, the gripper, the STM acquisition unit, the touch processing node, and the sensing node. First, the supervisor commands the robot to take a pre-defined pickup pose, so that a berry hanging on a branch will be positioned between the gripper fingers. Once the manipulator reaches this position, mono-frequency excitation is started, and the system enters the pre-sensing `APPROACH_UNTIL_TOUCH` state, where the gripper incrementally closes until contact is detected by the touch controller. A contact event triggers the transition to `CONTACT_CONFIRMED`, followed by sweep excitation of the sensorized system. For the training phase, 25 CSV files containing three sweep signals (9600 samples in each file) were saved for the quantitative data analysis. Each file contained three sweeps to ensure data integrity in case certain samples were lost during transmission, and only one full sweep was chosen per trial. In total, the training dataset contained 300 trials (25 sweep trials $\times$ 12 strawberries). During testing, 25 consecutive sweep responses were passed to the sense controller with the ordinal regression model online. This sensing node extracted the selected spectral feature and performed classification to estimate fruit ripeness.

Based on the estimated results, the supervisor enters the `SELECT_POLICY` state and chooses the appropriate grasping strategy. If the fruit is predicted to be acceptable for harvesting, the system proceeds to `FINAL_GRASP`, where the gripper applies the grasp

policy associated with the predicted ripeness. In particular, ripe fruit (Day 1.6–3.5) leads to a firmer grasp of 2 N, whereas overripe fruit (Day 3.6–5) leads to a softer grasp of 1 N in order to reduce the risk of bruising or mechanical damage. The Wittenstein industrial force/torque sensor provided the precise force feedback in this stage. If the fruit is predicted as unripe (Day 1–1.5), the robot releases the fruit, and the sequence terminates without harvesting. After a successful final grasp, the manipulator executes the detachment motion, and the system transitions to DONE state.

3.4.2 Subsystems

At the subsystem level, the Franka manipulator operates through the states HOME, KNEEL, and PICKUP to enable a structured motion sequence for approach and harvesting. The gripper state machine starts in OPEN, transitions to APPROACH_CLOSE, and enters HOLD once contact is established. From this state, the gripper selects either FORCE_GRASP or SOFT_GRASP depending on the estimated ripeness, and remains in the selected mode during harvesting until the fruit is detached. In parallel, the STM module alternates between IDLE, MONO, and SWEEP, providing the excitation modes required for touch detection and ripeness estimation. The touch controller processes mono-frequency data to detect shifts in the dominant response associated with initial contact, while the sense controller analyzes sweep data and estimates the condition of a sample (UNRIPE, RIPE, or OVERRIPE). So, the proposed architecture separates low-level sensing and actuation from high-level decision making, thus allowing the harvesting behavior to be adapted online according to the condition of each fruit.

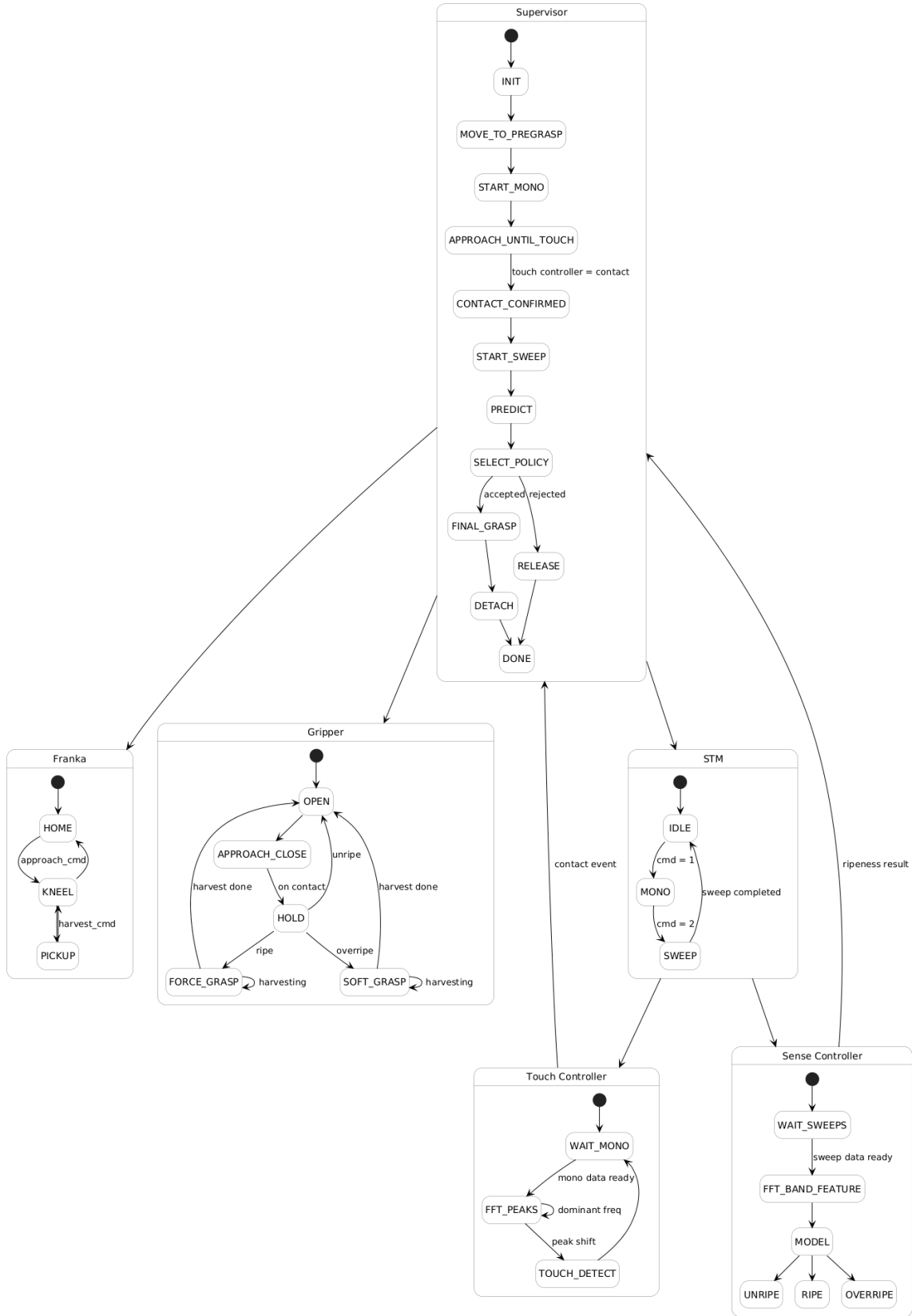


Figure 3-4: State machine diagram for the robotic harvesting workflow.

3.5 Data Analysis

3.5.1 Spectral Feature Extraction Framework

For each of the 25 repeated sweep measurements for a given strawberry sample, a differential FFT signal was calculated $D_i(f) = \text{FFT}(Tx)_i - \text{FFT}(Rx)_i$. This output provides insights into how the absorption properties of a berry alter, depending on its mechanical properties at each ripeness stage. To obtain a robust sample-level representation and avoid pseudo-replication, the differential spectra were first averaged across repeated measurements $\overline{D}(f) = \frac{1}{N} \sum_{i=1}^N D_i(f)$ and parametric spectral features were then extracted from the averaged differential spectrum over the 50–1000 Hz range, covering the excitation band (100–800 Hz) $x_{\text{feat}} = f(\overline{D}(f))$. In this way, each strawberry sample was represented by a single feature vector derived from its mean differential spectral response. The extracted parametric features include descriptors of the global spectral shape, including the Area Under the Curve (*AUC*), *Kurtosis*, and *Centroid*, together with point-based descriptors such as peak frequency (*PeakFreq*) and amplification (*PeakAmp*), and minimum frequency (*MinFreq*) and amplification (*MinAmp*). In the following, I describe the best-performing feature in terms of ripeness tracking based on its correlation with the day.

3.5.2 Correlation Analysis

To choose the primary descriptor of strawberry ripeness, a non-parametric Spearman correlation analysis was performed to assess monotonic relationships between each extracted spectral feature (continuous variable) and ripeness day (ordinal variable). From the results that are provided in Table 3.1, it can be seen that the *BandRatio_{LM}* gives the strongest negative correlation with a coefficient of -0.815. This parameter was calculated as a ratio between the area under the curves in 10–300 Hz (**L**ow) and 300–500 Hz (**M**id) frequency bands:

$$\text{BandRatio}_{LM} = \frac{AUC_{Low}}{AUC_{Mid}}$$

Table 3.1: Spearman correlation results

AUC	PeakFreq	PeakAmp	MinFreq	MinAmp	Kurtosis
0.538	-0.502	0.672	-0.438	0.091	0.133
Centroid	PosAUC	NegAUC	BandRatio_LM	BandRatio_MH	BandRatio_LH
-0.346	0.685	-0.532	-0.815	0.482	-0.373

Such a high correlation can be explained by the fact that ripening changes the strawberry tissue mechanically; that is, its firmness decreases, resulting in increased damping characteristics. Those changes often appear as a redistribution of spectral energy across frequency bands. Because the *BandRatio* captures the global shape of the vibrational response spectrum, it can be more stable and robust to noise in contrast to local features that are based on one frequency bin (e.g. *PeakAmp*, *MinFreq*). Besides that, soft biological tissue tend to affect lower frequencies more prominently due to their low damping. That is why the low- and mid-bands provide more informative results than the higher frequencies. As the berry ripens, more energy is concentrated in the mid-band and less in the lower band, and the *BandRatio_{LM}* captures the balance between them. Since ripening is associated with reduced firmness and increased viscoelastic damping, the mechanical response of the berry may shift toward lower effective frequencies while mid-frequency components become more strongly damped. As a result, the relative transmitter–receiver spectral difference decreases in the low-frequency band compared with the mid-frequency band.

3.5.3 Mixed-Effect Model

Because the same strawberries were observed over 5 days, resulting in longitudinal data, the measurements cannot be considered independent. In this case, each strawberry sample is deemed to have a unique identity, which is reflected as an unmeasured source of variance. This sample-to-sample variability can be viewed as a *random effect* in the *mixed-effect model*. The *fixed effect*, on the other hand, is berry’s ripeness stage (day), which is modeled as a categorical variable that is expected to be common across samples. With this mixed-effect model, it is possible to estimate one common

ripening pattern in $BandRatio_{LM}$ across 5 ripening stages, still allowing each sample to have its own baseline and accounting for correlation between the repeated trials from the same berry. This formulation also reflects the experimental intent that the chosen strawberries represent a sample from a broader population of strawberries that have similar ripening patterns.

To assess the significance of the random effect, the Likelihood-Ratio Test (LRT) was performed to compare a linear mixed-effects model with strawberry as a random intercept against a corresponding linear fixed-effects-only model. The random effect was not statistically significant ($LR = 0.745$, $p = 0.194$) and the estimated group variance was close to zero ($\sigma_{group}^2 = 4.5 \times 10^{-4}$), suggesting comparable within-day responses across the 12 strawberries. This result signifies that adding a random intercept does not improve the model’s performance significantly. On the other hand, the fixed effect of day was highly significant overall ($LR = 91.322$, $p = 6.90 \times 10^{-19}$), emphasizing the $BandRatio_{LM}$ varied systematically as the berries ripened. This was further supported by pairwise comparisons using the Wald test, which indicated significant differences between nearly all days, with the weakest separation observed between Day 4 and Day 5 ($p = 4.21 \times 10^{-2}$).

A closer look at the distribution of $BandRatios$ between the low and mid-frequency ranges reveals a notable trend of decreasing value of the chosen feature with the increase in the berry’s age (Fig.3-5(A)). The estimated marginal means (EMMs) of the fixed effect follow a monotonic decrease from Day 1 to 4, and a slight increase on Day 5. The absence of a significant random effect implies that strawberry-specific baseline variation was negligible relative to the effect of ripeness day. Therefore, it is possible to aggregate the responses from all strawberry samples by day and visualize the average differential FFT, as in Fig.3-5(B). The differential response of each day shows how the energy within low and mid-frequency bands redistributes as the berry becomes more mature and starts resonating at lower frequencies and absorbing more energy at mid frequencies. That being said, the chosen descriptor seems to effectively capture a shared ripening-related response, which supports the expectation that the resulting model may generalize to other strawberries with comparable

ripening dynamics, making it sample-agnostic for precision agriculture practices.

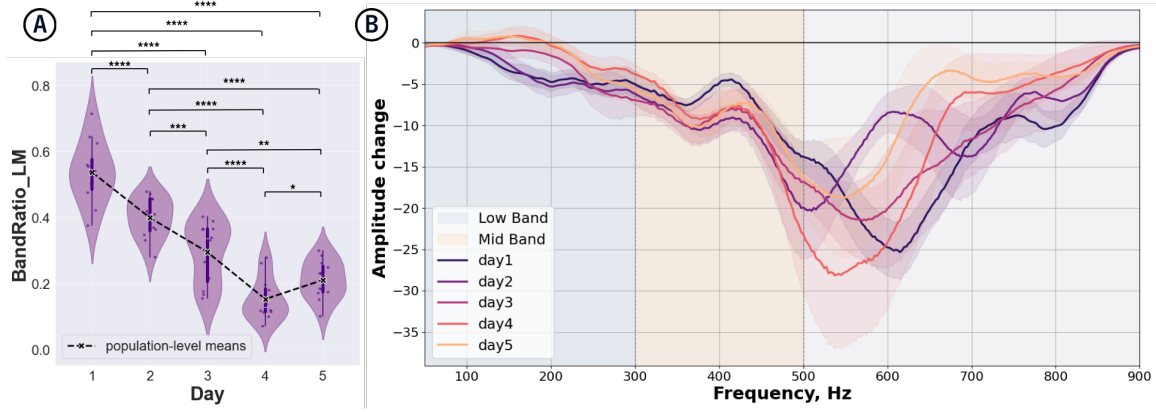


Figure 3-5: Vibrational response of the strawberries at each ripeness stage. (A) Distribution of $BandRatio_{LM}$ values for individual samples across days, with the fitted population-level means overlaid. (B) Aggregated differential FFT spectra representing the averaged energy distribution across days. Shaded envelopes indicate standard deviation, and shaded background regions denote the low- and mid-frequency bands used to compute $BandRatio_{LM}$.

3.6 Ordinal Logistic Regression

To predict the ripeness stage from the selected descriptor, $BandRatio_{LM}$, ordinal logistic regression was chosen as a primary classification model. To represent ripening as a biologically meaningful progression rather than as an exact temporal label, the days were converted into three ordered ripeness stages: *unripe* (Day 1–1.5), *ripe*, and *overripe*. This is because strawberries stored for the same number of days may still exhibit variability in their mechanical condition. Grouping neighboring days into broader ripeness stages therefore reduced sensitivity to day-to-day variability and improved interpretability. Therefore, ordinal logistic regression with $BandRatio_{LM}$ as the predictor and ripeness stage as the ordered response was chosen to account for the natural ordering of the resulting classes.

We can write the functional form of the ordinal regression as follows

$$\log\left(\frac{P(Y_i \leq j | x_i)}{1 - (P(Y_i \leq j | x_i))}\right) = \theta_j - \beta x_i, \quad j = 1, 2$$

where Y_i is the ordered ripeness stage of sample i , x_i is the predictor $BandRatio_{LM}$, β is the regression coefficient, and θ_1, θ_2 are the thresholds separating two adjacent ripeness classes. For the three classes

$$P(Y_i = \text{unripe} | x_i) = \sigma(\theta_1 - \beta x_i)$$

$$P(Y_i = \text{ripe} | x_i) = \sigma(\theta_2 - \beta x_i) - \sigma(\theta_1 - \beta x_i)$$

$$P(Y_i = \text{overripe} | x_i) = 1 - \sigma(\theta_2 - \beta x_i)$$

where $\sigma(t) = \frac{1}{1+e^{-t}}$, $\beta = -24.17$, $\theta_1 = -11.38$, and $\theta_2 = -6.23$. The fitted coefficient $\beta = -24.17$ was negative, indicating that decreasing $BandRatio_{LM}$ shifts the predicted probability from *unripe* toward *ripe* and *overripe*. Two threshold parameters θ_1, θ_2 were estimated to convert the ripeness scale into the three ordered classes. For each sample, the fitted model returned the probabilities of belonging to each ripeness class, and the final class prediction was assigned according to the highest predicted probability.

The trained ripeness model was subsequently transferred to the ROS-based sensing controller for online validation. To ensure consistency between offline training and online inference, the same signal-processing pipeline was reproduced in the sensing node: incoming transmitter and receiver signals were transformed into the frequency domain, combined into a differential FFT spectrum, and reduced to the selected descriptor $BandRatio_{LM}$. The fitted model parameters obtained offline were then embedded into the ROS node, thus, allowing the controller to compute ripeness predictions directly from the online measurements in real time.

Chapter 4

Results

4.1 Contact Detection

Touch was identified by monitoring changes in the vibrational spectrum. However, comparable spectral variations may also result from external disturbances, including vibrations induced by the gripper's active motion. To isolate the intrinsic spectral signature of touch, I conducted preliminary experiments when the gripper 1) touched the strawberry and 2) gripper moved to the same position but without the berry, as shown on a spectrogram in Fig.4-1A. From the spectrogram, it was possible to identify a threshold that filters the touch event from external noise at a specific frequency range. Specifically, by comparing the peak amplitudes at around 600 Hz and 800 Hz, it was possible to identify a moment of contact establishment. These frequencies also provide isolation from the moving gripper noise. The measurements from the HEX21 force sensor were acquired synchronously. The output was comparable to its standard deviation of 0.071 N and, thus, did not capture the touch signature (Fig.4-1B).

To define the final stopping condition for the gripper movement, I took a closer look at the FFT magnitude spectrum at both contact and no-contact events (Fig.4-1C). From the spectra, it can be seen that at the moment of contact, the peak amplitude in the 600-650 Hz window decreases significantly, while in the 800-850 Hz window, it increases. This result allowed to formulate a condition that triggers a touch event: when the peak amplitude at 600-650 Hz is less than that at 800-850 Hz,

and when the peak amplitude at 800-850 Hz is greater than 20. The second clause of the condition ensures that the touch event is filtered out of the gripper noise, avoiding false detection at a lower threshold or excessive force at a higher threshold.

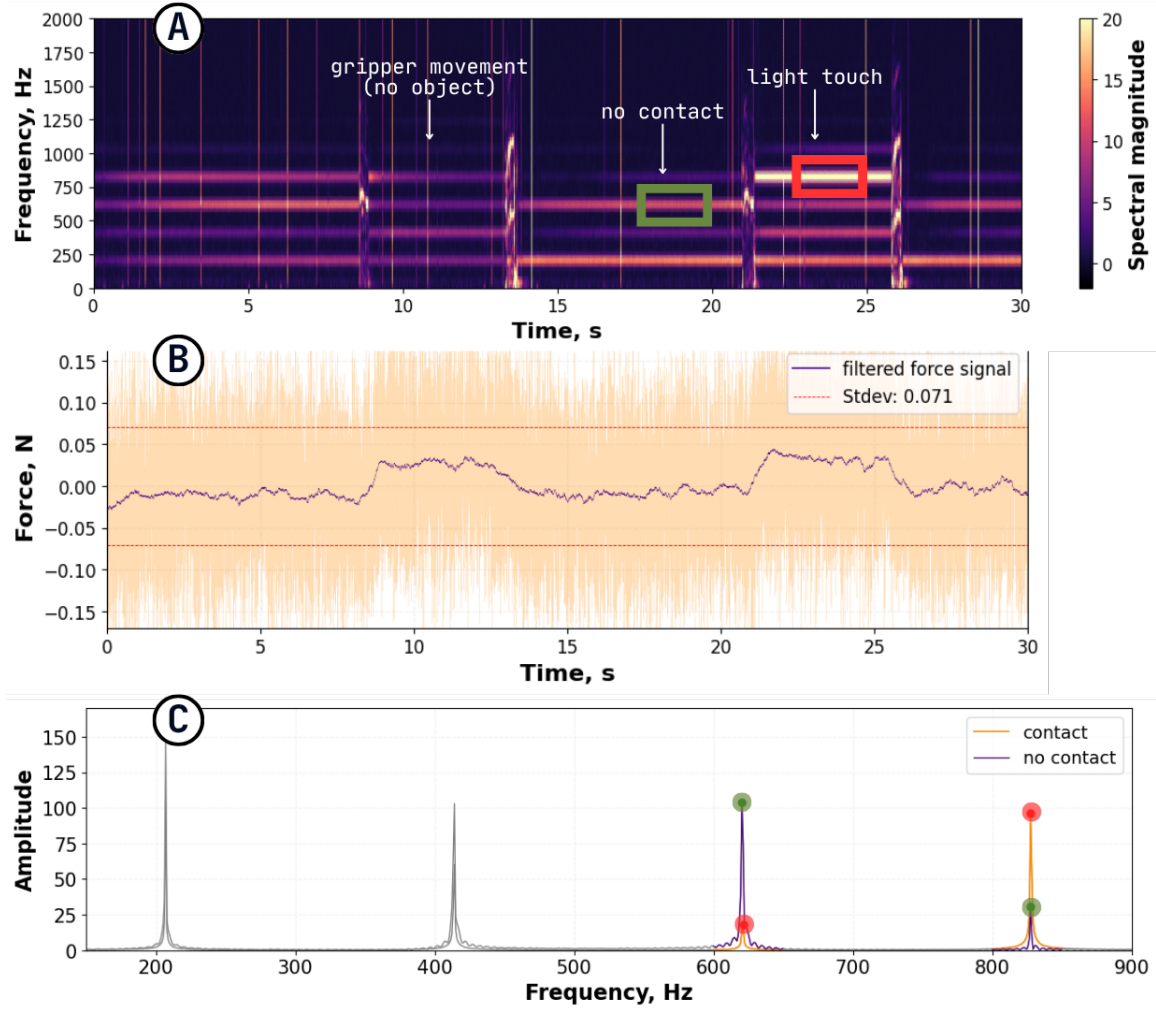


Figure 4-1: Contact detection. (A) Spectrogram distinguishing contact from gripper motion noise. (B) The force signal remains within the noise level and does not detect contact. (C) FFT shows decreased amplitude at 600–650 Hz and increased amplitude at 800–850 Hz at contact.

4.2 Strawberry Ripeness Estimation

As the contact was established, the system followed up on the ripeness estimation by exciting a strawberry with sweep signals and inferring its ripeness stage with ordinal

logistic regression.

4.2.1 Cross-Validation Results

Prior to evaluating generalization to unseen strawberries, I performed leave-one-strawberry-out cross-validation using Sample as the grouping variable, accounting for repeated measurements across ripening days. In each of 12 folds, all observations belonging to one strawberry were held out for testing, while the ordinal logistic regression model was trained on the remaining strawberries. This ensured that the test data always came from a berry that was entirely unseen during model fitting, thereby avoiding optimistic bias caused by within-sample dependence. The model achieved an overall classification accuracy of 80% (Fig.4-2). Class-wise recall was 83% for unripe, 75% for ripe, and 83% for overripe. Most importantly, all misclassifications were confined to adjacent ripeness stages, that is, there was no direct confusion between unripe and overripe. This indicates that the model preserved the ordinal ripening structure well, even when it was not exactly correct. This result showed a promise to test the model on uniquely new strawberry samples and validate its performance.

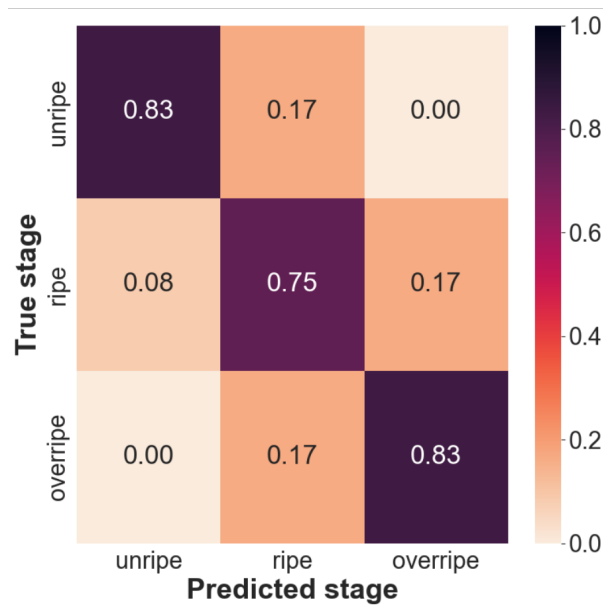


Figure 4-2: Confusion matrix showing LOSO cross-validation results.

4.2.2 Validation: Selective Harvesting Scenario

The final stage of this work was to emulate a selective strawberry-harvesting scenario, in which the robot infers the required grasping force from a non-destructive ripeness estimate. This integrated system represents the main contribution of the thesis. In this workflow, the robot first establishes a light contact with the strawberry, then estimates ripeness using active vibrational feedback, and finally selects the grasping strategy accordingly. An example of successful robot performance during detachment of a ripe strawberry sample (Day 3) is shown in Fig. 4-3.

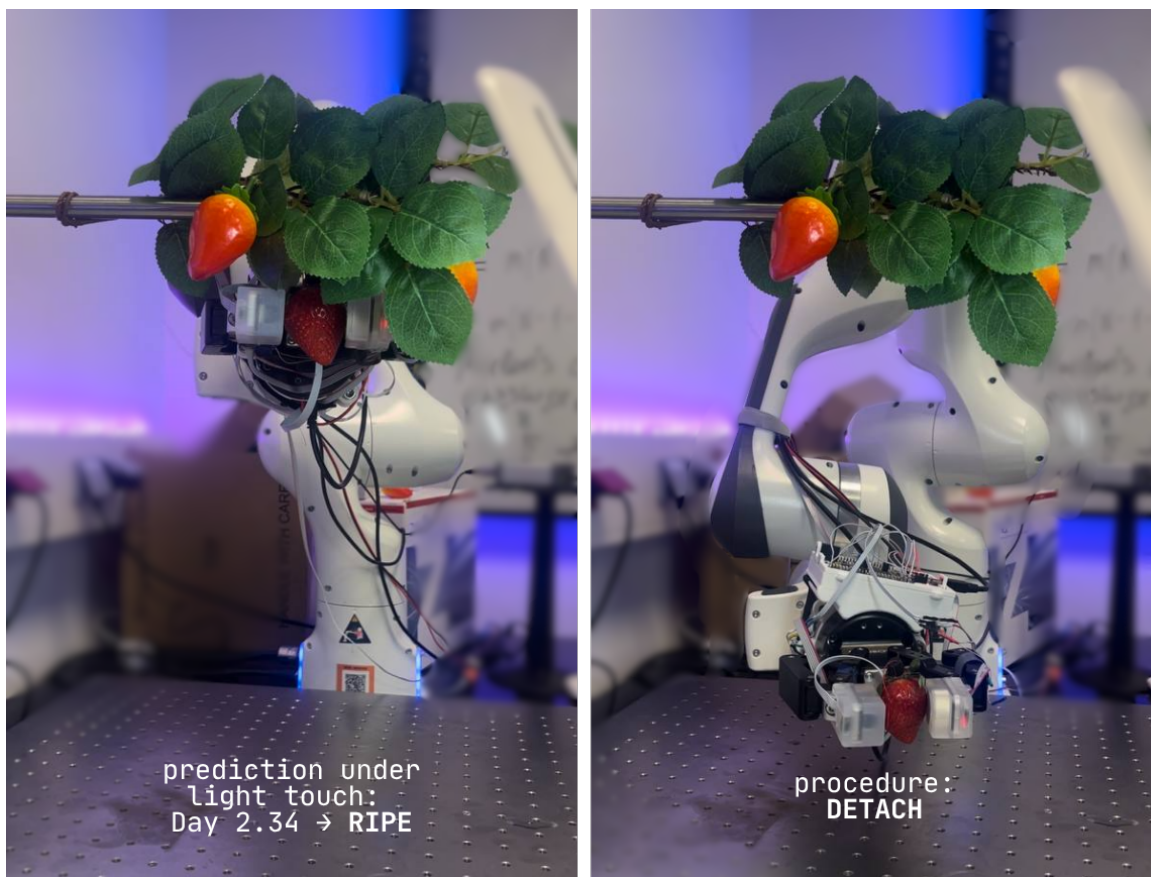


Figure 4-3: Simulating the selective harvesting scenario: the robot is executing the detachment of a ripe strawberry sample.

For this experiment, 9 strawberries were prepared and divided into three ripeness groups: *unripe*, *ripe*, and *overripe* (Fig. 4-4(B)). The samples were randomly selected and attached to the artificial branch using magnets, following the same procedure as in the training data collection. A trial was considered successful when the contact

force remained below the noise level of the industrial force/torque sensor and the ripeness stage was classified correctly. In each trial, the robot executed the selective strawberry-harvesting workflow with adaptive grasping, as described in Sections 3.4.1 and 3.4.2. Notably, all pre-emptive classifications were performed under light-touch conditions, for which the industrial force/torque sensor reported no measurable normal force. This signifies the high sensitivity and repeatability of the proposed vibro-tactile sensor.

Despite the structural and mechanical variability inherent to a natural object such as a strawberry, the proposed method achieved a validation classification accuracy of 71% on unseen samples (Fig. 4-4(A)). Class-wise performance was highest for the *unripe* samples, which were correctly identified in 83% of cases, while the recalls for the *ripe* and *overripe* classes were 69% and 67%, respectively. Importantly, misclassifications were limited to adjacent ripeness stages. These results indicate that the selected tactile descriptor and the ordinal classification model were able to capture ripeness-related mechanical differences with moderate-to-high reliability under realistic harvesting conditions.

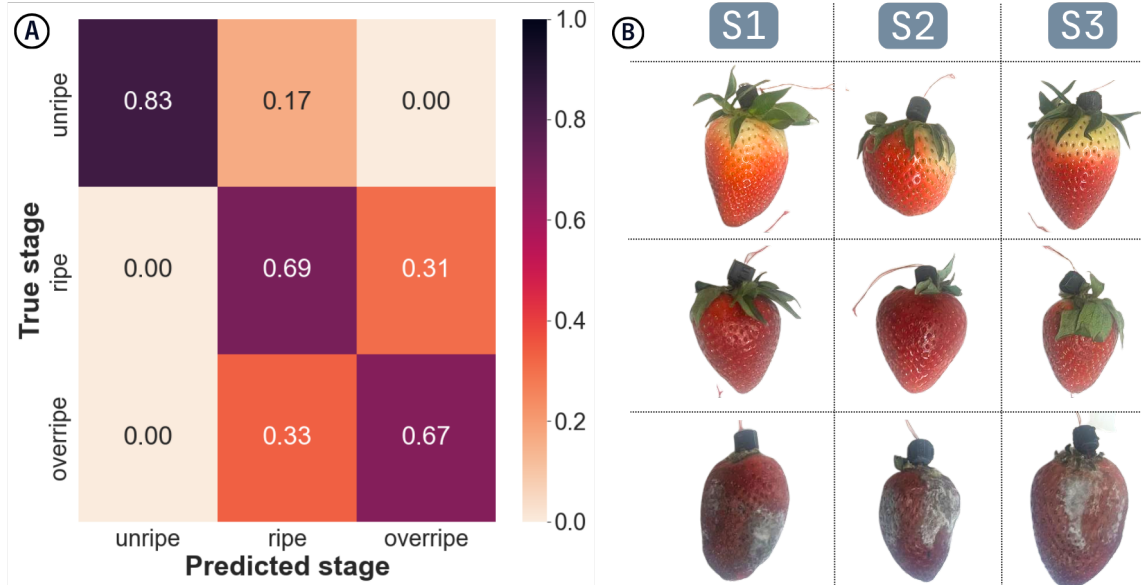


Figure 4-4: Validation on unseen strawberries. (A) Confusion matrix showing validation results. (B) The strawberry samples that were used to test the final force-adapting system.

Chapter 5

Discussion and Conclusion

Endowing robotic systems with dexterity and the sense of touch similar to human haptics is the core of safe and effective interaction with the world. In this research, I demonstrated how a robot can handle delicate objects, such as strawberries, with care. To perform this task, information about the mechanical properties of the strawberry structure at each ripening stage was utilized. The tactile sensing system enables accurate touch detection, strawberry ripeness estimation, and adaptive grasping while remaining affordable and simple to manufacture. The experiments showed that the active vibration sensing enables the successful classification of strawberry samples based on their ripeness stage.

The key **contributions** of this thesis are as follows:

1. Developed a highly sensitive active vibro-tactile sensor with dual objectives: contact detection with a mono frequency signal and ripeness (firmness) estimation with a sweep signal. Under a light touch, this configuration enables non-destructive, accurate berry ripeness assessment with a potential for large-scale use.
2. Integrated the tactile system with a robotic arm and gripper to imitate the realistic selective strawberry harvesting scenario. Unlike traditional systems that rely on visual feedback, the proposed system is based on pure tactile feedback, thus avoiding the problems related to occlusion and dark environments.

3. Established and validated a complete tactile perception-to-action pipeline for ripeness-aware harvesting, including differential spectral analysis, descriptor selection, statistical validation, and real-time deployment of the trained ripeness model in a ROS-based controller for adaptive grasping.

The main limitation of this study is the relatively small sample size, which may restrict the statistical strength of the conclusions and limit the generalizability of the trained models. Although the random effect of strawberry identity was found to be negligible within the present dataset, higher generalization would likely require a substantially larger and more diverse population of berries, covering broader variability in cultivar, internal structure, and ripening trajectories. Another limitation is that ripeness labels were derived from storage-day-based grouping rather than from direct destructive measurements of firmness or biochemical composition. As a result, the assigned ripeness stages represent a practical approximation of physiological state rather than an exact ground truth. In addition, the validation experiments were carried out under controlled laboratory conditions, using an artificial branch. While this setting enabled repeatable testing, further work is required to assess robustness under more realistic agricultural conditions. Finally, although the proposed tactile descriptor and ordinal classification model showed promising performance, the observed validation ceiling suggests that the remaining limitation lies not only in model selection but also in the intrinsic overlap between ripeness classes and the variability of natural strawberries.

To address these limitations, future work should focus on expanding the dataset to include a larger and more diverse set of strawberries of multiple cultivars and broader ripening variability. The use of direct mechanical or biochemical ground-truth measurements, such as with a destructive MT test, would also strengthen the labeling of ripeness stages and reduce ambiguity associated with storage-day-based categorization. In addition, validation should be extended to more realistic harvesting environments. Finally, richer spectral representations and multimodal fusion with vision may further improve robustness and predictive accuracy.

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